

Review

Remote Sensing of Mine Site Rehabilitation for Ecological Outcomes: A Global Systematic Review

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Abstract: The mining industry has been operating across the globe for millennia, but it is only in the last 50 years that remote sensing technology has enabled the visualization, mapping and assessment of mining impacts and landscape recovery. Our review of published literature (1970–2019) found that the number of ecologically focused remote sensing studies conducted on mine site rehabilitation increased gradually, with the greatest proportion of studies published in the 2010–2019 period. Early studies were driven exclusively by Landsat sensors at the regional and landscape scales while in the last decade, multiple earth observation and drone-based sensors across a diverse range of study locations contributed to our increased understanding of vegetation development post-mining. The Normalized Differenced Vegetation Index (NDVI) was the most common index, and was used in 45% of papers; while research that employed image classification techniques typically used supervised (48%) and manual interpretation methods (37%). Of the 37 publications that conducted error assessments, the average overall mapping accuracy was 84%. In the last decade, new classification methods such as Geographic Object-Based Image Analysis (GEOBIA) have emerged (10% of studies within the last ten years), along with new platforms and sensors such as drones (15% of studies within the last ten years) and high spatial and/or temporal resolution earth observation satellites. We used the monitoring standards recommended by the International Society for Ecological Restoration (SER) to determine the ecological attributes measured by each study. Most studies (63%) focused on land cover mapping (spatial mosaic); while comparatively fewer studies addressed complex topics such as ecosystem function and resilience, species composition, and absence of threats, which are commonly the focus of field-based rehabilitation monitoring. We propose a new research agenda based on identified knowledge gaps and the ecological monitoring tool recommended by SER, to ensure that future remote sensing approaches are conducted with a greater focus on ecological perspectives, i.e., in terms of final targets and end land-use goals. In particular, given the key rehabilitation requirement of self-sustainability, the demonstration of ecosystem resilience to disturbance and climate change should be a key area for future research.

Keywords: mine site rehabilitation; reclamation; ecological restoration; remote sensing; mining

1. Introduction

The practice of ecological restoration aims to facilitate a level of native ecosystem recovery following disturbance impacts on a scale, ranging from ecosystem degradation to complete ecosystem destruction [1,2]. Within this broad area of study, one particular sub-discipline has emerged. With a

specific focus on the rehabilitation of landscapes following mining, post-mine rehabilitation is clearly distinct from non-mining restoration projects due to the high-levels of disturbance. As a result, recovery objectives are more likely aligned with new (novel) or hybrid ecosystems made up of native and exotic species that provide acceptable levels of stability and ecosystem functionality [3].

The importance of post-mine rehabilitation is identified by governments across multiple jurisdictions, who have introduced legislation that require mining companies to achieve specified standards for reconstructed landforms, topsoil, vegetation, and water quality. In the United States, the introduction of the Surface Mine Control and Reclamation Act of 1977 [4] represented one of the first federal government regulations to enforce rehabilitation standards, including the filling of remaining voids and pre-specified end land-uses [5]. Since then, numerous jurisdictions have implemented similar legislation administered by governments, aiming for best practice and including key features such as financial assurances, progressive rehabilitation, and targets that are safe, stable, non-polluting and ecologically sustainable [6–11].

The most common way for mining companies to demonstrate rehabilitation success and provide confidence for mine closure is through ecological monitoring [12]. This is typically achieved using ground-based transect and quadrat monitoring methods that are robust and repeatable, and subject to an appropriate level of scientific scrutiny [13–16]. Such an approach provides data on a range of conditions, from the initial stages of landform reshaping, to the demonstration of vegetation cover development and the evidence of complex ecosystem function and structure. Ground-based monitoring methods are often labor-intensive exercises and although technically precise, these programs are constrained spatially, temporally, and financially. While the aim for ground monitoring is a study design that is statistically representative of the sampled population, for the above reasons, these programs tend to sample a small proportion of the landscape, and their effectiveness might be limited due to this scale factor. The International Society for Ecological Restoration (SER) has developed an ‘ecological recovery wheel’ monitoring tool to guide restoration projects and quantify the trajectory of recovery in comparison to analogue native ecosystems [1]. This tool helps to define the attributes and sub-attributes that are necessary to determine successful ecosystem recovery, by focusing on the key areas of structural diversity, species composition, physical conditions, external exchanges, ecosystem function, and absence of threats. Although mined land rehabilitation that returns novel ecosystems might not be appropriate to compare directly with natural analogues [12,17,18], the tool developed by the SER offers an appropriate choice of metrics to measure and quantify the success of rehabilitation efforts.

In contrast to ground monitoring programs that are constrained by small areas, remote sensing offers the opportunity to monitor at a landscape scale to either compliment ground surveys, or replace them entirely. In the last two decades the science of remote sensing and spatial analysis underwent a fundamental shift, with new advances in earth observation and drone technology providing opportunities for rapid and cost effective assessments of multiscale landscape changes, and ecosystem development of restoration and rehabilitation projects [19,20]. However, due to the inherently heterogeneous nature of the rehabilitated landscapes, these areas can be challenging to monitor remotely. As a constructed landscape, rehabilitation is typically made up of discrete patches of vegetation in different stages of development, with underlying soil characteristics and landform slopes and topography that can vary significantly over short distances; particularly when compared to neighboring unmined land [12]. Additionally, rehabilitation managers often vary inputs, such as seed mixes, topsoil depth, and site preparation techniques, resulting in high levels of spectral heterogeneity within and between patches, across post-mining landscapes [21–30]. Nonetheless, the advantage of a remote sensing approach that uses discrete classification at fine spatial scales, is the potential to characterize the heterogeneity and the patterns associated with fine scale rehabilitation history, such as topsoil distribution, landform contour banks, and seeding patterns, using innovative classification techniques [31]. Moreover, a number of studies have shown the possibility of taking

advantage of spectrally unique rehabilitation targets, using high temporal resolution provided by earth-observation satellites [32].

The capacity for remote sensing to convey the complexity of post-mine rehabilitation and the ecological drivers that lead to successful plant establishment and growth, and to mine closure is not comprehensively addressed across the literature. A number of review papers have examined the connection between remote sensing and mining, including fine scale land cover classifications [19], drone monitoring of restoration projects [20,33], and mine impacts [34,35]. Additionally, other review studies have assessed how restoration projects applied ecological attributes using ground monitoring [17,36]. However, there are no review papers that have assessed the role remote sensing has played in the ecological assessment of post-mine rehabilitation. Given the advances in remote sensing technology over the last 50 years and the future trajectories for the areas requiring rehabilitation globally, this paper represents an important and timely contribution.

We undertake a systematic review to assess the current status of remote sensing studies of vegetation dynamics on mine site rehabilitation between 1970 and 2019. We start by characterizing the sensors, platforms, and classification methods used, and the locations and types of mapped resources. We then discuss the key question of how closely remote sensing studies approximated the monitoring of ecological attributes and success of mine site rehabilitation. Using the International Society for Ecological Restoration's ecological recovery wheel monitoring tool as a template [1], we categorize past studies to assess how researchers approached assessments of rehabilitated landscapes. In particular, what are the ecological attributes that remote sensing measures and where are the research gaps? Are there ecological attributes that remote sensing is not able to measure effectively? We conclude by providing a set of recommendations to guide future research.

2. Materials and Methods

2.1. Search Criteria

We conducted an online search on 23/01/2020 applying a systematic approach to our literature review, using Scopus to search for all papers published between 1970 and 2019. The fifty-year period was chosen to adequately capture the beginning of earth observation through to the current era, and thus provide insight into the progress of rehabilitation assessments from relatively coarse resolution satellites to modern, high spatial and temporal sensors. We used the following search query string:

(TITLE-ABS-KEY ("remote sensing")) AND (TITLE-ABS-KEY ("mine" OR "mining" OR "mined")) AND (TITLE-ABS-KEY ("restoration" OR "reclamation" OR "rehabilitat*" OR "revegetat*")) AND (TITLE-ABS-KEY ("vegetat*" OR "eco*" OR "cover" OR "environment*")) AND NOT (TITLE-ABS-KEY ("data mining")).

For the purposes of this study, we used the definitions for rehabilitation, restoration, reclamation, and revegetation, derived from the International principles and standards for the practice of ecological restoration [1]. Many of these terms are used interchangeably throughout the literature. Herein, we use the term 'rehabilitation' to describe the process of landform reconstruction and reinstatement of a desired level of ecosystem function and vegetation structural development following mining disturbance.

Following the initial online Scopus search, papers were selected for the review based on a four-stage process. First, papers that met the above Scopus search criteria were selected and downloaded if they were relevant to the fields of remote sensing and mine site rehabilitation, published in peer review journals (conference proceedings, books, and non-peer reviewed articles were not included) and published in the English language. Second, papers were shortlisted according to their suitability to the review topic and based on the following criteria. Papers were required to:

- include remote sensing as a core component of the study;
- have mine rehabilitation as either a feature of the study or a discrete mapping class (regional or catchment scale studies that generate Land Use Land Cover (LULC) maps were not included);

- make a novel contribution to the ecology of mine site rehabilitation and successional focus, rather than mapping studies that might have focused more broadly on LULC;
- demonstrate a primary focus on vegetation rather than other biophysical attributes such as soil or water.

We eliminated a significant number of remote sensing papers that did not directly focus on rehabilitation. For example, many papers assessed the direct impacts of mining on land cover, using change detection at regional scales (e.g., [37,38]), while other studies showed a greater emphasis on soil assessments [39–41].

Third, we searched Google Scholar, Web of Science, and ScienceDirect, based on the following word combinations: “remote sensing mine rehabilitation”, “remote sensing mine reclamation”, “remote sensing mine closure”, “remote sensing mine restoration”, and “remote sensing mining land cover” to cross check the Scopus search and determine if any relevant papers were missed. We took the first entries until there were no relevant entries after five pages.

Fourth, during the reading and review process, any new and relevant literature discovered within the reference lists were included in the review.

2.2. Data Compilation

The aims and objectives of each paper were summarized, in addition to the year of publication, Country, region, and location of the study. We compiled a database to summarize a number of variables including commodity, study type, sensors, spatial extent, classification method, temporal scale, and indices used (Table 1).

Mine ‘Commodity’ was recorded for each study to determine if remote sensing studies favored any particular commodities. Copper, zinc, gold, silver, and nickel mines were all grouped into the category ‘Metalliferous’ and small mines extracting hard-rock, calcareous sandstone, bentonite, and perlite were grouped into the category ‘Quarry’. The type of extraction method was also recorded and included open-cut, underground, small-scale artisanal mining, borehole, open pit, strip mining, and quarry. However, this was not included in the final assessment, since the majority of studies were open-cut (86%) and mine type can largely be inferred from commodity. Note that only one study was conducted on an underground coal mine assessing the subsidence impacts on vegetation [42].

Papers were categorized based on the ‘Study Type’ that was undertaken. Ecological studies were those that used remote sensing to gain a deeper understanding of the ecological processes that are occurring in rehabilitated areas. Often these studies are novel and combine remote sensing with ecological field data in an innovative way. This category was further separated into ecological studies that used field data (‘Ecol (Field Obs)’ and ecological studies that did not use field data (‘Ecol (No Field Obs)’). Other categories within the Study Type variable were ‘Land Cover’ assessments, ‘Theoretical’ studies ($n = 2$) that employed method development, ‘Review’ papers ($n = 4$) and papers that developed decision support system tools (‘DSS’), generally aimed at policy development ($n = 2$).

The ‘Sensors’ that were used in each study were recorded and then summarized into broad groups, based on the predominant sensor. These categories included: ‘EO Low’ Earth observation low resolution (>30 m); ‘EO Medium’ Earth observation medium resolution (5–30 m); ‘EO High’ Earth observation high resolution (<5 m); ‘Drone’ for drones using optical sensors (i.e., include various methods such as Structure from Motion (SfM) point clouds to produce Digital Elevation Models (DEMs) and the classification of multispectral imagery) and thermal sensors; ‘Terrestrial Light Detection and Ranging (LiDAR)’, ‘Aerial Optical’ (True-Colour/Multispectral), ‘Aerial Hyperspectral’, ‘Aerial LiDAR’, ‘SAR’ (Synthetic Aperture Radar), and ‘Handheld Hyperspectral’ sensors. Note that we found no studies that used drone LiDAR or drone hyperspectral sensors.

Table 1. Metadata used to categorize each study in the review. Each study was given a class according to the variables below. * Study Type was also classified according to the International Society for Ecological Restoration (SER) ecological recovery wheel attributes (not listed here).

				Variables				
Commodity		Study Type *		Sensors	Spatial Extent	Classification Method	Temporal Scale	Index
Categories/Class	- Coal	- Ecological (with Field Observations)	- EO Low (>30 m)	- Regional scale (multiple Mine sites, > 50 km ²)	- GEOBIA	- Uni-Temporal	- Single VI-NDVI	
	- Metalliferous		- EO Medium (5–30 m)					- Supervised
	- Bauxite	- Ecological (without Field Observations)	- EO High (<5 m)	- Mine site scale (1 Mine site, 10–50 km ²)	- Unsupervised	- Tri-Temporal	- Multi VI	
	- Iron-Ore		- Drone Optical (RGB/MS/Thermal)					- Spectral
	- Mineral Sand	- Land Cover	- Terrestrial LiDAR	- Block scale (1–2 age-classes of rehabilitation, 1–10 km ²)	- Time Series	- Decadal		
	- Oil Sands	- Review	- Aerial Optical (RBG/MS)				- Hyperspectral sensors	
	- Phosphate	- Theoretical	- Aerial					
	- Uranium	- Decision Support System	- Hyperspectral sensors					
	- Quarry		- Aerial LiDAR					
	- Sulphur		- SAR					
			- Handheld Hyperspectral sensors					

The ‘Spatial Extent’ of each study was categorized into three classes that best reflected the range of studies used in the project. This included the ‘Regional scale’, which were studies that included multiple mine sites ($>50 \text{ km}^2$), the ‘Mine Site Scale’ that were focused on the assessment of one entire mine site and surrounding areas ($10\text{--}50 \text{ km}^2$), and the ‘Block Scale’, which were studies that focused on 1–2 age-classes of rehabilitation or one rehabilitated block of land ($1\text{--}10 \text{ km}^2$). There were no studies that assessed rehabilitation at the continental or global scale.

‘Classification Method’ was summarized into four broad groups—‘GEOBIA’ for those studies employing Geographic Object-Based Image Analysis (GEOBIA) to segment and classify images based on image-objects rather than pixels; ‘Supervised’ for studies that used a variety of methods including machine learning algorithms such as Random Forests, Support Vector Machines, and boosted classification and regression trees (CART). Other supervised techniques included Maximum Likelihood, k-Nearest Neighbor (k-NN) and Artificial Neural Network (ANN) Classifiers. Studies that used training samples to classify images were also included in the Supervised class. ‘Unsupervised’ methods included Iterative Self-Organizing Data Analysis (ISODATA), self-organization cluster analysis (ISOCUST—from IDRISI), and ISOSEG (using k-Means). Studies that used methods such as LandTrendr were classed separately as ‘Spectral Time-Series’. The studies that were classed as ‘Manual’ were those that did not use any of the above methods and manually created classes, either by digitizing polygons or using spectral indices to extract features such as vegetation cover, tree canopies, or bare areas.

‘Temporal Scale’ of the studies was summarized by the following classes—‘Uni-Temporal’ for those studies using a single image for the analysis; ‘Bi-Temporal’ when two images were used; ‘Tri-Temporal’ for those studies using 3 images; and ‘Multi-Temporal’ when multiple images were used. These studies spanned 1–2 decades (this can be a time-series [43] or 5+ images within the same decade [44]); and ‘Decadal’ was used to describe studies which used multiple images spanning multiple (>2) decades. Generally, these studies employed time-series analysis and change detection for LULC assessments [45].

The spectral indices (‘Index’) used were summarized for each study. We wanted to know which vegetation index (VI) was the most commonly used and if any particular index was more successfully employed, compared to others. Studies were grouped into ‘Single VI–NDVI’ for those that only used Normalized Differenced Vegetation Index (NDVI), ‘Single VI–Other’ for studies that used a vegetation index apart from NDVI, ‘Multi-VI’ when studies used more than one index (note that all of these included the use of NDVI) and ‘Sensor Bands Only’ for those studies that used spectral bands without applying band ratios.

To determine contribution to ecological outcomes, each study was categorized based on the attributes of the ecological recovery wheel designed for the monitoring of restoration projects by the International Society for Ecological Restoration (SER) [1]. In particular, we used the six attributes and eighteen sub-attributes developed in Principle 3 that are suited for the monitoring of recovering or rehabilitated ecosystems. Each study was categorized according to the most suitable attribute and sub-attribute that best represented the primary objective of the study. The six attributes included—Absence of Threats, Physical Conditions, Species Composition, Structural Diversity, Ecosystem Function, and External Exchanges. Note that of the total 99 papers in the review, those classed as review papers ($n = 4$) and decision support system tools (DSS) papers ($n = 2$) did not generate any ecological research outcomes and were, therefore, omitted from the ecological recovery wheel assessment, leaving a total of $n = 93$ papers. The total number of papers for each category were rescaled to the five-point scale featured in the ecological recovery wheel. This was based on the maximum number of studies for the spatial mosaic sub-attribute, which was the most common study type. In order to further explore the ecological recovery wheel as a remote sensing monitoring tool, we assessed each attribute and sub-attribute and ranked these on the 1–5 scale for the potential for a remote sensing monitoring approach on post-mine rehabilitation. Where remote sensing has a high potential to monitor a sub-attribute, these were ranked a maximum of 5. A moderate and low potential

were ranked a 3 and 2, respectively, and scores were ranked zero when a remote sensing approach was unlikely to contribute to monitoring outcomes for mine site rehabilitation.

Finally, we recorded overall map accuracies (OMA %) which were grouped according to the Index used.

3. Results

The online search using Scopus, Google Scholar, Web of Science, and ScienceDirect, resulted in a total of 333 papers; of which 193 research and 4 review papers were assessed according to their suitability. Using our search criteria, we shortlisted a total of 99 papers for the final review comprising 93 research papers, 2 decision support system (DSS) and 4 review articles.

Over time, the number of papers published increased exponentially, with 5 (5%) papers published in the decade 1970–1979, 3 (3%) in 1980–1989, 6 (6%) in 1990–1999, 18 (18%) in 2000–2009, and 67 (68%) published in 2010–2019 (Figure 1). Early papers from the mid-1970s were all studies conducted on rehabilitated coal mines in the United States of America (USA) using Landsat sensors. Overall, the USA accounted for 21 (21%) studies, Australia—17, China—13, Canada—9, Germany—5, and Brazil, Bulgaria, Finland, Greece, India, Indonesia, Italy, Papua New Guinea, Laos, Poland, Russia, South Africa, Spain, and Turkey all had less than 5 studies each (Figure 1A). Remote sensing studies were mostly conducted on coal mines (62%), followed by metalliferous mines (17%), quarries (5%), and bauxite, iron-ore, mineral sand, oil sands, phosphate, sulfur, and uranium (less than 5%) (Figure 1B).

Figure 1C shows that Landsat sensors were the dominant choice of sensor in 50% of studies over the 50-year period. However, over time a greater number of sensors were used, especially between 2010–2019. This was particularly the case in 2017, 2018, and 2019, when drones were used in 25% of studies, aerial hyperspectral in 8%, aerial optical in 4%, and high-resolution earth observation Satellite Pour l'Observation de la Terre (SPOT) in 5%, and WorldView in 3% of studies (Figure 1C).

Interestingly, research conducted in the last decade covered a greater diversity of SER ecological sub-attributes, when compared to the entire 1970–2019 period. While spatial mosaic studies (represented by predominantly LULC studies) dominated over the 1970–2019 period with 63% of studies, the 2010–2019 decade saw an emergence of new studies with a focus across a broader range of sub-attributes. These included remote sensing papers that assessed topics such as productivity/cycling (14%), landscape flows (11%), desirable plants (3%), invasive species (3%), and habitat links (2%) (Figure 1D).

Over the five decades, the types of studies varied, with 36% of research papers attributed to ecological studies with field data, 37% land cover studies, and 18% ecological studies without field data (Figure 2A). In general, studies were dominated by earth observation (EO) low spatial-resolution sensors (55%), with drone-based sensors being the second highest (10%), followed by aerial hyperspectral sensors (8%), EO high (7%), and EO medium (6%) (Figure 2B). The spatial extent for more than half (52%) of the studies was at the mine site scale, with comparatively fewer studies at the regional scale (30%) and the block scale (13%) (Figure 2C). For the temporal scale, the studies were mostly uni-temporal (36%) or decadal (23%), and the classification methods tended to focus on supervised (43%) or manual methods (33%) (Figure 2D,E).

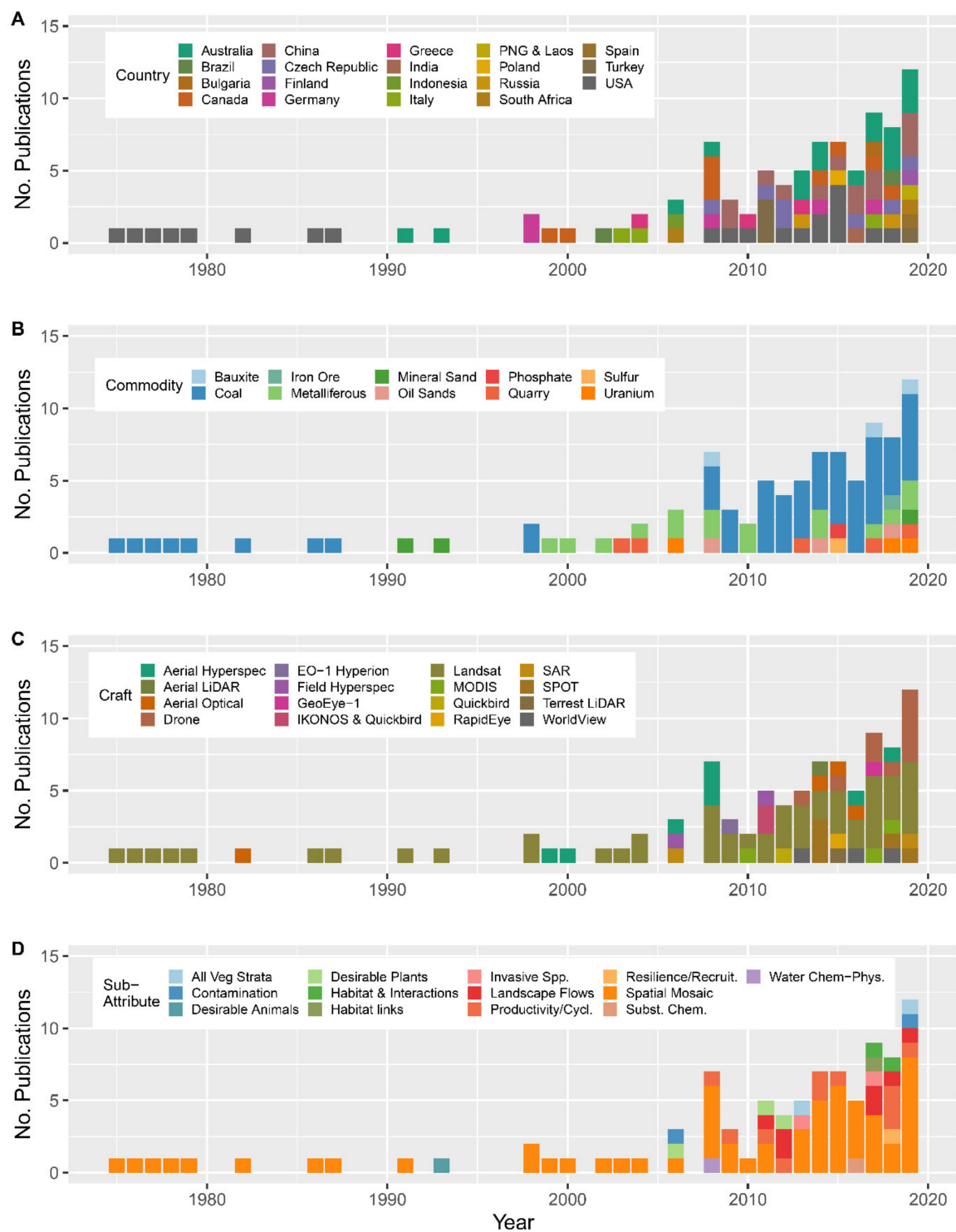


Figure 1. Stacked bar charts showing the number of publications for each year, according to the country of study (A), the commodity (B), the primary craft used for the assessment (C), and the sub-attributes taken from the SER ecological recovery wheel (D).

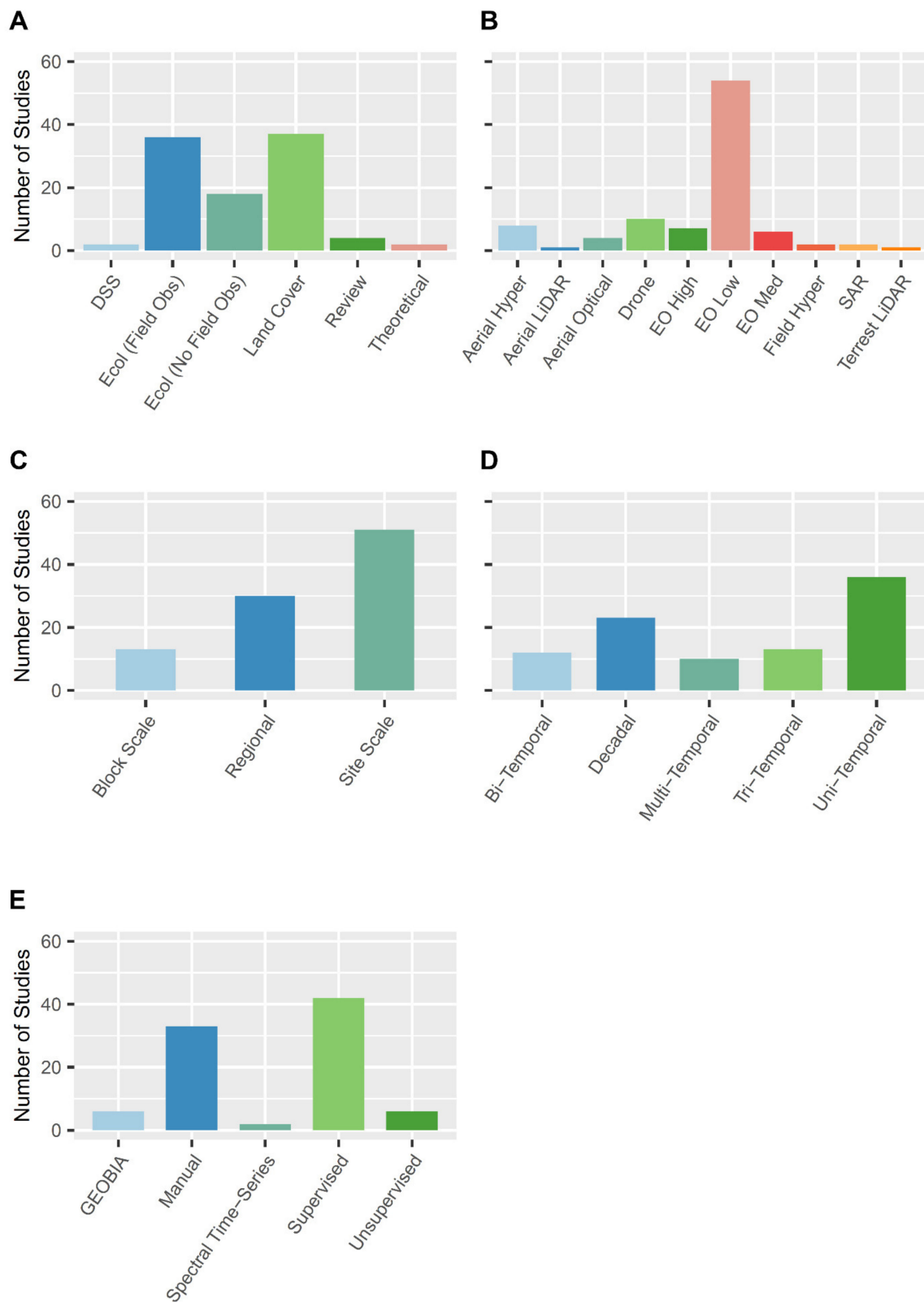


Figure 2. Summary statistics for the 99 publications reviewed showing the type of study (A), type of sensor (B), spatial extent of study (C), temporal scale (D), and classification methods employed (E).

Figure 3A shows the SER ecological recovery wheel categorized for the 93 research papers. (Note that of the total 99 papers, 4 review papers and 2 DSS were omitted from this assessment). The total number of papers for each category were rescaled, based on the maximum number of studies for a single sub-attribute, which was 59 (63%) for the sub-attribute spatial mosaic. As a result, all other sub-attributes were rescaled to 1 or below on the ecological recovery wheel scale (Figure 3A). This demonstrated that the literature was dominated by LULC studies, while a smaller proportion focused on ecosystem function (productivity/cycling) (11%) or external exchanges/landscape flows (7%). All other attributes were either under-represented or not represented at all.

It is our opinion that remote sensing has the potential to address 16 of 18 sub-attributes in the ecological recovery wheel, as shown in Figure 3B. Twelve sub-attributes scored a maximum of 5, suggesting that remote sensing is capable of assessing metrics including resilience/recruitment, invasive species, desirable plants, and all vegetation strata. Desirable animals scored 3 indicating a moderate capacity for assessment. All three physical conditions sub-attributes scored 2, suggesting a low capacity, while gene flows and all trophic levels scored zero, suggesting remote sensing is not suitable (Figure 3B).

Figure 4 shows the frequency of spectral indices used as a total of the reviewed publications. Normalized Differenced Vegetation Index (NDVI) was the most common index used, with 44 studies (44%) employing the index. A total of 43 studies (43%) did not employ an index and used sensor bands, most commonly within a supervised classification (47%). The orthogonal indices tessellated cap and principal component analysis (PCA) were used in 9 studies (9%) and 4 studies (4%), respectively; while 7 studies (7%) used soil adjusted vegetation index (SAVI). Six (6) studies used enhanced vegetation index (EVI), normalized moisture difference index (NMDI), and simple ratio (SR), while 5 studies used fractional vegetation cover (Frac Veg). A total of 6 narrow band indices were used with hyperspectral imagery, while 7 indices were used with standard color (RGB) imagery from drone studies.

Of the total studies, 37 quantified overall map accuracy using error matrices, with an average overall accuracy of 84% and a range from 41% to 99% (Table 2). Fourteen publications used NDVI as the only index with an average overall map accuracy of 83% and a range between 52% and 99%. The majority of these studies used GEOBIA classification, along with high-resolution earth observation imagery and did not use field data to validate classifications. Thirteen of the studies used sensor bands with an average overall map accuracy of 85% and a range from 41% to 98%. Comparatively fewer studies used multiple vegetation indices (including NDVI) (6) and single vegetation indices (not NDVI), with an average overall map accuracy of 86% and 74%, respectively (Table 2).

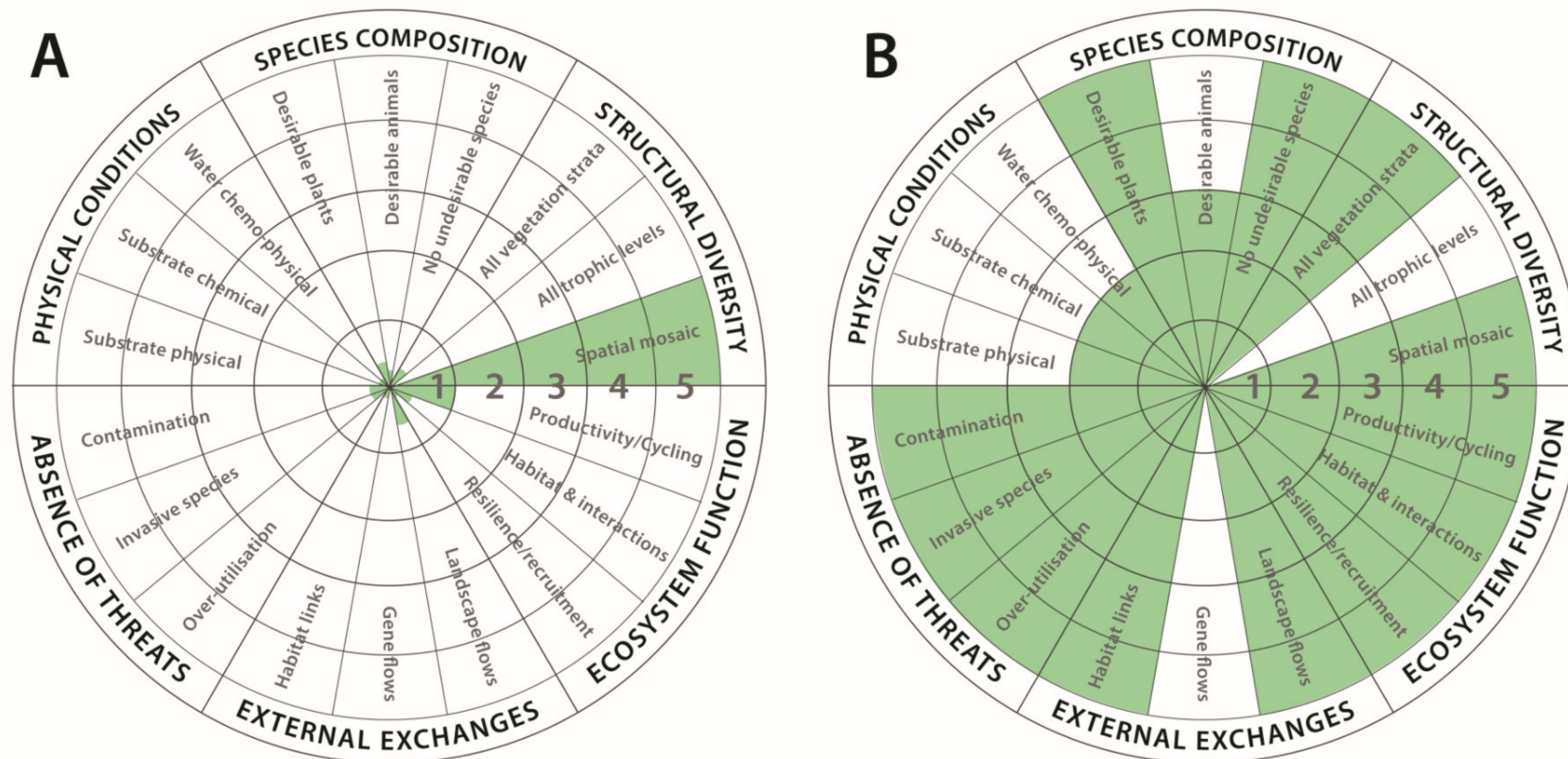


Figure 3. Remote sensing studies plotted on the ecological recovery wheel for monitoring projects (International Society for Ecological Restoration (SER)) based on their primary objective and rescaled by the sub-attribute spatial mosaic which had the highest number of studies at 59 (A). Potential application of remote sensing opportunities for monitoring in mine site rehabilitation (B). This figure was adapted from the ecological recovery wheel, accessed at <http://seraustoralasia.com/wheel/wheel.html>.

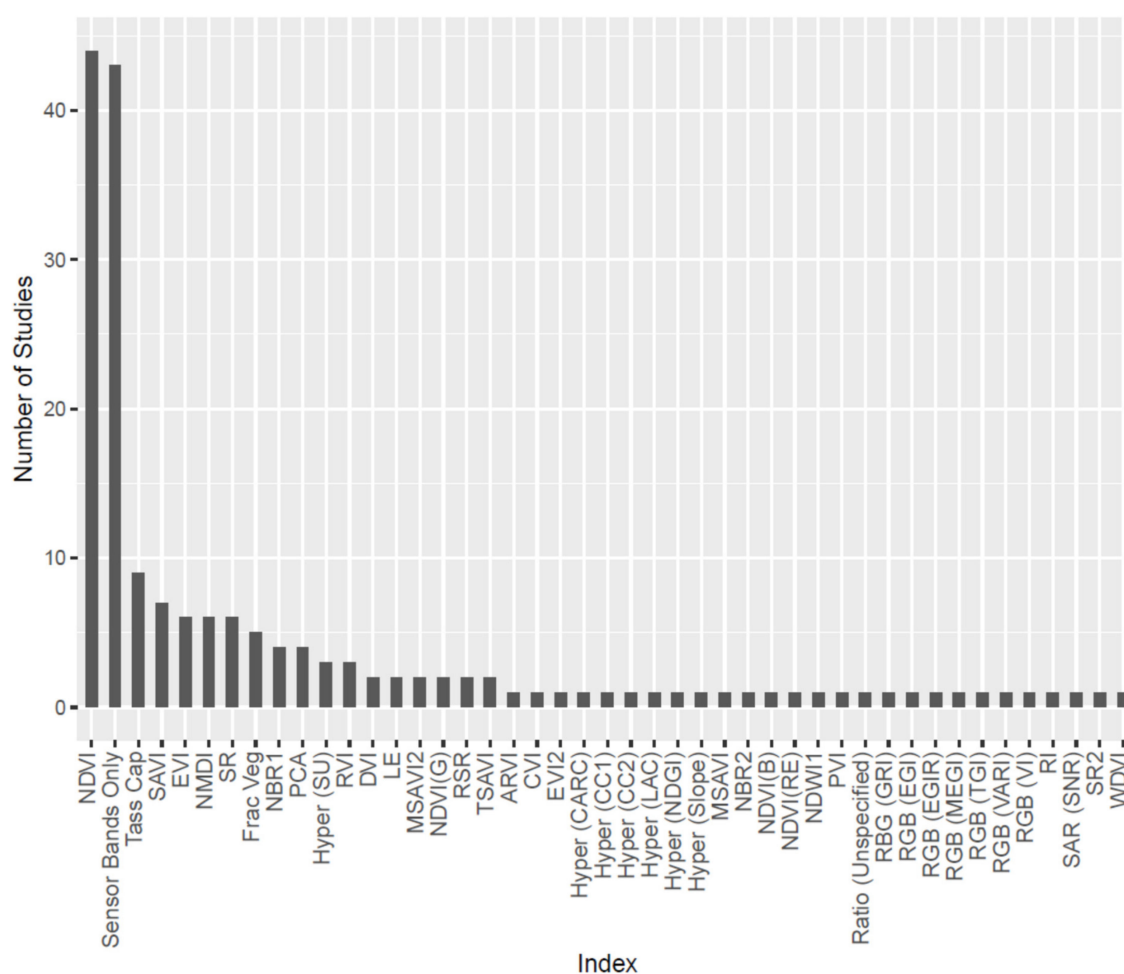


Figure 4. The frequency of indices used. Note that a number of studies used multiple indices within one publication. Hyper = Hyperspectral imagery narrow band indices, and RGB = derived from color red green blue imagery. For a list of index names see Table A1.

Table 2. Summary of overall map accuracies indices taken from studies in the review that quantified overall map accuracies.

Index Category	n (Values)	n (Publications)	Average (%)	Min (%)	Max (%)	SD
Multi VI (NDVI+)	19	6	86	45	97	12.9
Sensor Bands Only	97	13	85	41	98	12.3
Single VI NDVI	33	14	83	52	99	12.0
Single VI Other	9	4	74	52	91	15.0
Total/Overall	158	37	84	41	99	13.0

Figure 5 shows an alluvial chart that represents the proportions of data within each variable and the interconnectedness between variables (columns) and categories (rows). The black lines (nodes) represent each category, and the length of the node represents the proportion of publications. For example, the decade 2010–2019 produced the highest number of studies, and most of these publications were produced by the USA, Australia, Canada, and China. A large proportion of the studies produced in the USA were on coal mine rehabilitation, mostly conducted at the site and regional scale. On the right hand side of the alluvial chart, the dominance of the ecological attribute structural diversity and corresponding sub-attribute spatial mosaic is apparent (63%), while important metrics such as resilience/recruitment represent only 1% of studies (Figure 5).

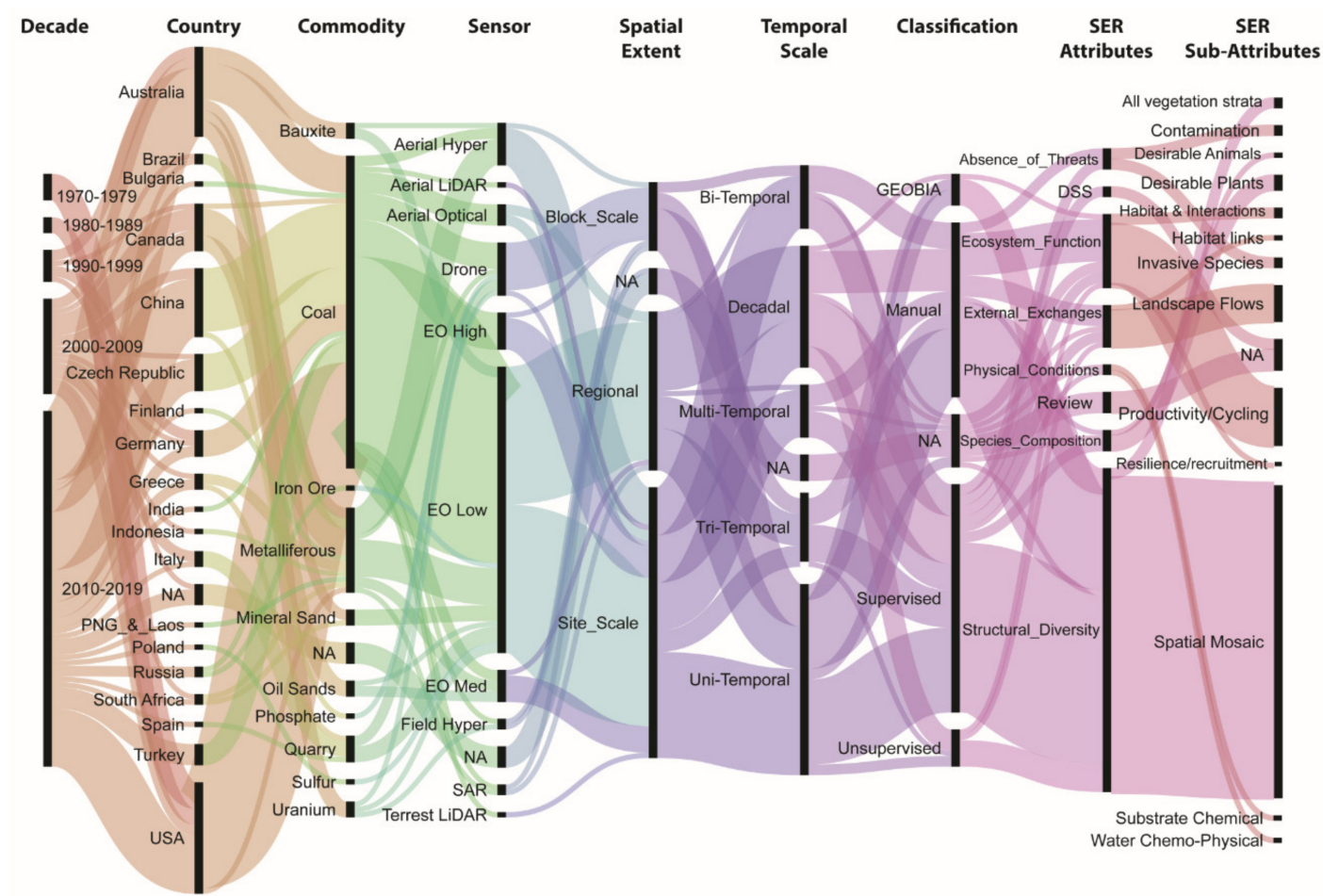


Figure 5. Alluvial chart demonstrating the proportions within variables and the correlations between variables. From Left to Right: Decade of publication, Country of study, Commodity, Sensor used in study, Spatial Extent, Temporal Scale, Classification method, ecological attribute, and ecological sub-attribute. NA = review papers, DSS, and theoretical papers.

4. Discussion

4.1. Overview

The use of remote sensing to monitor mine site rehabilitation is well established, with studies conducted across 19 different countries on a diverse range of commodity types and using a variety of sensors and platforms. Since the early 1970s, scientists have looked to remote sensing technology to gauge land cover change and quantify rehabilitation outcomes associated with mining impacts [34,46–48]. However, the vast body of research for the last five decades shows little evidence that remote sensing has provided practical outputs that capture the key ecological characteristics required for ecological monitoring, and the application of rehabilitation science. Although there was a greater diversity of studies in the 2010–2019 decade, we found that overall, studies paid little attention to the importance of the rehabilitation process, ecosystem development and functioning, and the final goals and objectives of rehabilitation, including mine closure. This is most clearly shown when studies were categorized using the Society for Ecological Restoration's (SER) ecological recovery wheel monitoring approach [1]. From the total 18 sub-attributes, 63% of studies focused on the spatial mosaic sub-attribute; while comparatively fewer studies addressed more complex topics such as ecosystem function, species composition, and absence of threats. Whereas the underrepresentation of studies on attributes associated with physical conditions was expected (since our review primarily focused on vegetation and actively filtered studies with a focus on substrate), the concentration of studies on spatial mosaic demonstrates the need for a greater understanding of the capacity for remote sensing to monitor rehabilitation success. This involves moving beyond historical approaches for remote sensing, which have commonly been on land-use and land-cover mapping to monitor change.

Interestingly, a review of 68 studies that assessed restoration success through ground monitoring campaigns also found that not all ecological monitoring attributes defined by SER were measured [17]. The most commonly assessed attributes included diversity, vegetation structure and ecological process attributes; while attributes that were poorly measured included those requiring long-time scales such as recruitment, integration with the landscape and self-sustainability. However, in a follow-up review nearly a decade later, Wortley et al. (2013) found that many studies had since addressed those attributes, indicating that the understanding of long-term processes was highly valuable to determining the success of restoration [36]. Coincidentally, attributes that require long-term data sets and can indicate the achievement of key goals of mine site rehabilitation such as sustainability (e.g., second-generation recruitment/resilience to disturbance events such as fire) are well placed for remote sensing assessments given spatial and temporal descriptive capabilities. Other attributes that are well placed for remote sensing assessments, and were under represented in the literature include attributes within ecosystem functioning, absence of threats, species composition, external exchanges, and structural diversity. Recent technological advances, coupled with improvements in our understanding of rehabilitation science, suggests that new approaches to remote sensing of rehabilitation are timely, needed, and achievable. Sensors such as hyperspectral and LiDAR have the potential to understand structural and developmental changes that are occurring across rehabilitated areas, while automated processing techniques and software are increasingly available for land managers and stakeholders. Furthermore, historical remote sensing archives can be used to “go back in time”, even if field data is unavailable to fill this important data gap commonly absent in field-based studies [49].

4.2. Chronological Development of Remote Sensing for Mapping Rehabilitation

The choice of sensors for rehabilitation monitoring projects always requires a trade-off between the available spatial and temporal resolution. The potential for remote sensing for quantifying rehabilitation extent and vegetation cover was initially demonstrated by a number of studies using early Landsat Multi Spectral Sensor (MSS) in comparative studies with aerial photography [47,48,50,51]. These pioneering early studies concluded that the new series of satellite earth observation sensors were well suited to land cover mapping, including the inference of vegetation development and

rehabilitation vigor [34]. Although now considered a low spatial and temporal resolution earth observation satellite, the Landsat series sensors were used consistently to characterize a range of rehabilitation features including land cover change [52–58], vegetation health [42,59], species level maps, including invasive species [60,61], vegetation biomass [62], successional development and age class differentiation [22,27,63], carbon sink calculations [64], disturbance and recovery change patterns [65], and surface temperature changes, as a function of vegetation cover and soil moisture properties [66]. Additionally, moderate to high spatial resolution earth observation sensors such as Satellite Pour l’Observation de la Terre (SPOT), IKONOS, Quickbird, RapidEye, GeoEye-1, and WorldView were typically employed in land cover studies, demonstrating the potential of classification methods using single or bi-temporal imagery [31,44,67–70], while other studies assessed rehabilitation for resilience and recovery from secondary disturbances [29,71].

Beyond the use of passive optical sensors, active sensors demonstrate the capacity for ecological monitoring of rehabilitation but are still relatively under-utilized. Bao et al. (2019) found that fusing WorldView-3 optical bands with Sentinel-1 SAR bands increased the correlation with on-ground measurements of above ground biomass and resulted in a model with a higher prediction accuracy ($r^2 = 0.79$, $RMSE = 22.82 \text{ gm}^{-2}$) compared to WorldView-3 and Sentinel SAR, separately in a rehabilitated semi-arid grassland in North China [24]. Other studies showed improvement in accuracy by including auxiliary non-spectral light detection and ranging (LiDAR) data. For example, Maxwell et al. (2015) showed that the inclusion of LiDAR had greater classification accuracy than using multispectral data which resulted in confusion between similar land cover classes such as unmined forest versus rehabilitated woodlands [72,73].

More recently, developments in high spatial and temporal resolution using drone-based sensors have contributed significantly to rehabilitation assessments. These studies showed the capacity for measuring vegetation canopies and woody species [74,75], vegetation health [76], impacts from fire disturbance [30], and cover changes over time, along with landform stability to demonstrate rehabilitation success at the block scale [77]. Vegetation structure was also assessed using Structure from Motion (SfM) derived 3D point clouds to measure canopy height and vegetation cover [25]. However, the accuracy of drone-derived products can be significantly impacted by a number of factors, such as season of capture, canopy shadows, camera settings, cloud shadows, and windy conditions that move foliage between captures [25,30,74,75]. Additionally, while drones are becoming increasingly popular, the cost of hardware and image capture, when compared with online free imagery from Sentinel and Landsat, might reduce their popularity in the longer term, and a lack of historic archival imagery is a key limitation.

The assessment of indices used showed the popularity of the Normalized Vegetation Difference Index (NDVI) as a tool for monitoring vegetation development on rehabilitated landscapes. In rehabilitation, as in other remote sensing studies, the NDVI is one of the most widely used indices for vegetation assessment [78]. The NDVI was used in 44% of studies and when employed as the only index ($n = 14$ studies) produced an average overall map accuracy of 83%. When NDVI was used in combination with one or more indices ($n = 6$ studies) overall average map accuracy increased marginally to 86% with a range of 45% to 97%. Interestingly when no vegetation indices were used ($n = 13$ studies), in predominantly supervised classification, overall map accuracy average was a high 85%, suggesting that while indices continue to remain popular, their use in classifying imagery is not essential. The diversity of indices used in papers assessing rehabilitation was notable, with 44 different spectral, orthogonal, SAR, and thermal indices used over the fifty-year period. Spectral indices derived from multispectral imagery (26 indices) were most common, followed by visible true color imagery (red green blue) (7 indices) and hyperspectral imagery (7 indices) (Table A1).

4.3. Recommendations for Operationalising Remote Sensing for Mine Site Rehabilitation

A number of studies demonstrated the increased scrutiny on rehabilitation outcomes following legislative changes, due to increased incentives for mining companies to report progressive rehabilitation

and demonstrate compliance to Government agencies. In the United States, the introduction of the Surface Mine Reclamation Act (SMCRA) of 1977 led to an initial surge in remote sensing studies developing methods to inventory rehabilitation efforts [22,47,48,50,51,79,80]. Similar legislation in other countries led to comparable studies in Canada [81,82], Poland [83], South Africa [58], Italy [84], Spain [85], Greece [53], China [86], and Australia [65,74,87,88].

Due to its popularity and availability, scientists from a broad range of disciplines are increasingly using remote sensing as a tool for environmental monitoring. However, remote sensing assessments of mine site rehabilitation require considerable knowledge and skill to interpret outputs of analysis and derive meaningful results. This is highlighted by a number of studies emphasizing the heterogeneous nature of mine site rehabilitation and the unique spatial and temporal challenges for remote sensing assessments [21–30]. Alternatively, the distinctive spectral, temporal and spatial patterns of rehabilitated landscapes provides opportunities for remote sensing to derive valuable ecological information. For example, progressive rehabilitation over a long period can result in a patchwork of different age-classes that potentially can be assessed with a single image to build change trajectories of ecological metrics such as vegetation cover, woody density, and species richness. Such assessments might be possible, but only with field-based knowledge such as establishment age, site preparation methods, seeding mixes, and reflectance values for endemic and exotic species. One key limitation we found was that less than half of the studies (43%) integrated ground-based field data with remote sensing data. Ground data are essential for calibrating and validating remotely sensed models and for testing correlations between ecological attributes such as vegetation cover. Another common limitation we identified was the assumption that increases in vegetation cover, identified by mapping vegetation cover, are equivalent to a final measure of success for mine site rehabilitation. While a measured increase in vegetation cover might indicate stability and show early stages of plant establishment, this represents just one metric in a suite of criteria that is needed to inform rehabilitation success. Importantly, this assumption ignores the value of desired plant species, absence of weeds, and the structural components of developing ecosystems that are essential to meet target community attributes required for end land-use and mine closure.

Several knowledge gaps can be addressed given the current state of remote sensing technology and image availability. Based on our knowledge of rehabilitation and remote sensing science, we make the following suggestions for future work:

- The monitoring of ecosystem function in the remote sensing literature is scant and is a key metric for rehabilitation success. In particular, the SER sub-attribute of ecological resilience requires further research. Given that one of the key aims for mine site rehabilitation is an ecosystem that is self-sustainable, the measurement and demonstration of resilience is one key area for future work [12,29]. This is particularly salient given that disturbances such as fire, drought, disease, floods, and storms are inevitable and predicted to increase, given climate change.
- Comparing baselines and reference sites to rehabilitated sites is a common approach used when monitoring for restoration success [1], and is often a requirement of ecological monitoring programs. However, the comparison between mined and unmined ecosystems was only addressed by a few notable exceptions [44,89]. Comparisons between unmined natural ecosystems versus rehabilitation will provide stakeholders with confidence in rehabilitation success and is important to support mine closure, and can be directly addressed using remote sensing.
- Studies showing long-term (decadal) development and achievement of ecological processes, such as structural canopy development [65], are required to confirm that a post-mining ecosystem is self-sustainable and resilient. A single snapshot or multiple snapshots in time provide little evidence of how rehabilitation is responding to long-term environmental fluctuations and changes over time. For example, many studies used NDVI as a proxy for vegetation vigor and rehabilitation success, however, this index is highly responsive to seasonal fluctuations. A time-series of NDVI provides more insight into rehabilitation performance rather than a uni-temporal assessment.

- Large-scale studies using long-term ground monitoring data integrated with remote sensing metrics to assess ecosystem development should be explored, given the availability of comprehensive ground monitoring data-sets that are often required by regulators to demonstrate rehabilitation progression.
- Regional or continental scale inventories of rehabilitation estates can provide industry-wide (and company-wide) perspectives on completed and still-to-be-completed rehabilitation projects.
- There are many examples of remote sensing approaches for measuring vegetation health, which could be used for rehabilitation monitoring that have been demonstrated in other disciplines, such as forestry [90].
- Field-based monitoring is still the most common approach used globally for assessing rehabilitation success, yet it is time-consuming, labor intensive, and expensive. In order for remote sensing to be further operationalized by mining companies and government regulators, researchers need to demonstrate which field-based metrics can be confidently derived using remote sensing techniques.

Throughout 50 years of remote sensing monitoring, there is yet to be a clear scientific consensus on the best approach for determining rehabilitation success through remote sensing methods. There are great opportunities for moving beyond the conventional land cover assessments and developing standardized approaches to measure a number of ecological attributes as defined by SER International standards. These opportunities could arise through the development of tools to assist rehabilitation practitioners and regulators, to measure short-term achievement of success criteria, or methods to quantify long-term success, including resilience to climate change and stochastic events.

5. Conclusions

Our review of the available literature indicates that over the past five decades, the number of ecologically focused remote sensing studies conducted on mine site rehabilitation increased gradually from the early 1970s to reach a peak in the 2010–2019 decade. Initial research was dominated by the Landsat series of satellites, through broad-scale land cover assessments, while the introduction of new earth observation and drone sensors enabled studies to explore more complex ecological metrics. However, the SER ecological monitoring attributes remain significantly underrepresented, and future research should focus on demonstrating the potential to measure sub-attributes associated with ecosystem function, absence of threats, species composition, and structural diversity. The average overall mapping accuracy for 37 studies that conducted error assessments was 84% and the NDVI was the most common spectral index, used in 44% of studies, with an average overall map accuracy of 83% when used as the solitary index. It is clear that the discipline is in the early stages of growth and there are significant opportunities for the assessment of progressive rehabilitation and achievement of end land-use targets. Given the comparatively recent rapid advances in sensor technology, processing software, and spatial analysis techniques, along with changing legal and social environments, the importance of developing standardized monitoring methods for gauging rehabilitation success is evident. Indeed, improvements in the characterization of ecological recovery through remotely sensed methods will lead to a number of positive outcomes; from increased efficacy of on-ground management, to increased stakeholder confidence throughout the progressive rehabilitation period, and at the time of mine closure.

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Appendix A

Table A1. Summary of indices used in the review. Hyper = Hyperspectral, Multi = Multispectral, SAR = Synthetic Aperture Radar, VIS = Visible. * Note that many studies used multiple indices.

Imagery Type	Index	Description	Formula	No. Studies *	% of Total Studies
Hyper	Hyper (CARC)	Carotenoid Content	$PSRI = (R680 - R500)/R750$	1	1.0
Hyper	Hyper (CC1)	Chlorophyll Content	$R695/R670$	1	1.0
Hyper	Hyper (CC2)	Chlorophyll Content 2	$(R850-R710)/(R850-R680)$	1	1.0
Hyper	Hyper (LAC)	Leaf Anthocyanin Content	$ARTI1 = (1/R700) - (1/R550)$	1	1.0
Hyper	Hyper (NDGI)	Normalised Differenced Green Index	$NDGI = (G - R)/(G + R)$	1	1.0
Hyper	Hyper (Slope)	Slope	$Slope = (NIR1125 - NIR935)/(NIR1125 + NIR935)$	1	1.0
Hyper	Hyper (SU)	Spectral Unmixing Endmember	-	3	3.0
Multi	ARVI	Atmospherically Resistent Vegetation Index	$ARVI = (NIR - (R - (B - R)))/(NIR + (R - (B - R)))$	1	1.0
Multi	CVI	Chlorophyll Vegetation Index	$NIR \times R/G^2$	1	1.0
Multi	DVI	Difference Veg Index	$DVI = NIR - R$	2	2.0
Multi	EVI	Enhanced Vegetation Index	$EVI = G \times (NIR - R)/(NIR + C1 \times R - C2 \times B + L)$	6	6.1
Multi	EVI2	Enhanced Vegetation Index 2	$EVI2 = 2.5 \times NIR - R/NIR + 2.4 \times R + L$	1	1.0
Multi	Frac Veg	Fractional Vegetation Cover	$FVC = (NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min})$	5	5.1
Multi	MSAVI	Modified Soil Adjusted Vegetation Index	$MSAVI = (NIR - R)/(NIR + R + L) \times (1 + L)$	1	1.0
Multi	MSAVI2	Modified Soil Adjusted Vegetation Index 2	$MSAVI2 = (2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - R)}) \times 0.5$	2	2.0

Table A1. Cont.

Imagery Type	Index	Description	Formula	No. Studies *	% of Total Studies
Multi	NBR1	Normalised Burn Ratio 1	$NBR = (NIR - SWIR2) / (NIR + SWIR2)$ (note SWIR2 = 2.11–2.29 μm on Landsat 8)	4	4.0
Multi	NBR2	Normalised Burn Ratio 2	$NBR2 = (SWIR1 - SWIR2) / (SWIR1 + SWIR2)$ (note SWIR1 = 1.57–1.65 μm SWIR2 = 2.11–2.29 μm on Landsat 8)	1	1.0
Multi	NDVI	Normalised Differenced Vegetation Index	$NDVI = (NIR - R) / (NIR + R)$	44	44.4
Multi	NDVI(B)	Normalised Differenced Vegetation Index (Blue)	$BNVI = (NIR - B) / (NIR + B)$	1	1.0
Multi	NDVI(G)	Normalised Differenced Vegetation Index (Green)	$GNVI = (NIR - G) / (NIR + G)$	2	2.0
Multi	NDVI(RE)	Normalised Differenced Vegetation Index (Red Edge)	$NDVI(RE) = (NIR - RE) / (NIR + RE)$	1	1.0
Multi	NDWI1	Normalised Differenced Wetness Index 1	$NDWI1 = (G - NIR) / (G + NIR)$	1	1.0
Multi	NMDI	Normalised Moisture Differenced Index	$NMDI = (NIR - SWIR1) / (NIR + SWIR1)$ (note SWIR1 = 1.57–1.65 μm on L8)	6	6.1
Multi	PVI	Perpendicular Vegetation Index	$PVI = NIR \times \sin x - R \times \cos x$	1	1.0
Multi	Ratio (Unspecified)	Vegetation Ratio	Unspecified (suspected NDVI)	1	1.0
Multi	RI	Regrowth index	$RI = NDVI_{(inner\ patch)} - NDVI_{(outer\ patch)}$	1	1.0
Multi	RSR	Reduced Simple Ratio	$RSR = SR \times 1 - SWIR - SWIR_{min} \times SWIR_{max} - SWIR_{min}$	2	2.0
Multi	RVI	Ratio Vegetation Index	$RVI = R / NIR$	3	3.0
Multi	SAVI	Soil Adjusted Vegetation Index	$SAVI = (NIR - R) / (NIR + R) + L \times (1 + L)$	7	7.1

Table A1. Cont.

Imagery Type	Index	Description	Formula	No. Studies *	% of Total Studies
Multi	SR	Simple Ratio	NIR/R	6	6.1
Multi	SR2	Simple Ratio 2	$NIR/SWIR$	1	1.0
Multi	TSAVI	Transformed Soil Adjusted Vegetation Index	$TSAVI = s \times (NIR-s \times R-a)/(a \times NIR + R-a \times s + X \times (1 + s2))$	2	2.0
Multi	WDVI	Weighted difference veg Index	$WDVI = NIR-s \times R$	1	1.0
No_Index	Sensor Bands Only		-	43	43.4
Orthogonal	PCA	Principal Components Analysis	-	4	4.0
Orthogonal	Tass Cap	Tasselated Cap	-	9	9.1
SAR	SAR (SNR)	Signal to Noise Ratio (not a spectral index)	$SNR = M/LSD$	1	1.0
Thermal	LE	Latent Energy Heat Flux	$LE = R_n \times (0.114 + 0.78 \times EVI + 0.004 \times LST)$	2	2.0
VIS	RBG (GRI)	Green Ratio index	$GRI = NIR/G$	1	1.0
VIS	RGB (EGI)	Excess Green index	$EGI = 2 \times G-R-B$	1	1.0
VIS	RGB (EGIR)	Excess Green Index Ratio	$EGIR = R/2 \times G \times 1000$	1	1.0
VIS	RGB (MEGI)	Modified Excess Green Index	$MEGI = 2 \times G-R$	1	1.0
VIS	RGB (TGI)	Triangular Greenness Index	$TGI = -0.5[(670-480)(R-G)-(670-550)(R-B)]$	1	1.0
VIS	RGB (VARI)	Visible Atmospheric Resistant Index	$VARI = (G-R)/(G+R-B)$	1	1.0
VIS	RGB (VI)	Vegetation Index	$VI = (2 \times G-R-B) - (1.4 \times R-G)$	1	1.0

Appendix B

Table A2. A summary of the 99 papers used in the study, sorted by year of publication.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
1	Wobber et al	[47]	1975	USA	Coal	EO Low	Landsat	Regional	Uni-Temporal	Manual	Y	Land Cover	Structural Diversity	Spatial Mosaic
2	Anderson & Schubert	[91]	1976	USA	Coal	EO Low	Landsat	Site Scale	Uni-Temporal	Supervised	Y	Land Cover	Structural Diversity	Spatial Mosaic
3	Anderson et al	[50]	1977	USA	Coal	EO Low	Landsat	Regional	Tri-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
4	Mamula	[48]	1978	USA	Coal	EO Low	Landsat	Regional	Uni-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
5	Brumbaugh	[51]	1979	USA	Coal	EO Low	Landsat	Regional	Uni-Temporal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
6	Game et al	[92]	1982	USA	Coal	Aerial Optical	Aerial_Optical	Site Scale	Multi-Temporal	Supervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
7	Irons & Kennard	[93]	1986	USA	Coal	EO Low	Landsat	Regional	Uni-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
8	Parks et al	[22]	1987	USA	Coal	EO Low	Landsat	Regional	Bi-Temporal	Supervised	Y	Land Cover	Structural Diversity	Spatial Mosaic
9	Phinn et al	[27]	1991	Australia	Mineral Sand	EO Low	Landsat	Site Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
10	Hill & Phinn	[63]	1993	Australia	Mineral Sand	EO Low	Landsat	Site Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Species Composition	Desirable Animals
11	Rathore & Wright	[34]	1993	NA	NA	NA	NA	NA	NA	NA	NA	Review	NA	NA
12	Felinks et al	[26]	1998	Germany	Coal	EO Low	Landsat	Site Scale	Bi-Temporal	Manual	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
13	Schmid et al	[21]	1998	Germany	Coal	EO Low	Landsat	Site Scale	Multi-Temporal	Supervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
14	Staeenz et al	[94]	1999	Canada	Metalliferous	Aerial Hyper	Aerial_Hyperspec	Site Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
15	Lévesque et al	[95]	2000	Canada	Metalliferous	Aerial Hyper	Aerial_Hyperspec	Site Scale	Uni-Temporal	Supervised	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic

Table A2. Cont.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
16	Almeida-filho	[45]	2002	Brazil	Metalliferous	EO Low	Landsat	Site Scale	Decadal	Unsupervised	N	Land Cover	Structural Diversity	Spatial Mosaic
17	Bonifazi et al	[84]	2003	Italy	Quarry	EO Low	Landsat	Regional	Uni-Temporal	Manual	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
18	Cutaia et al	[96]	2004	Italy	Quarry	EO Low	Landsat	Regional	Tri-Temporal	Manual	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
19	Ganas et al	[53]	2004	Greece	Metalliferous	EO Low	Landsat	Site Scale	Tri-Temporal	Supervised	N	DSS	NA	NA
20	Pfitzer et al	[97]	2006	Australia	Uranium	Field Hyper	Field_Hyperspec	NA	NA	NA	N	Theoretical	Species Composition	Desirable Plants
21	Trisasonkko et al	[98]	2006	Indonesia	Metalliferous	SAR	SAR	Regional	Uni-Temporal	Unsupervised	N	Land Cover	Structural Diversity	Spatial Mosaic
22	Weiersbye et al	[99]	2006	South Africa	Metalliferous	Aerial Hyper	Aerial_Hyperspec	Block Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Absence of Threats	Contamination
23	Antwi et al	[52]	2008	Germany	Coal	EO Low	Landsat	Site Scale	Bi-Temporal	Manual	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic
24	Gillanders et al	[55]	2008	Canada	Oil Sands	EO Low	Landsat	Regional	Decadal	Unsupervised	N	Land Cover	Structural Diversity	Spatial Mosaic
25	Halounová	[54]	2008	Czech Republic	Coal	EO Low	Landsat	Regional	Tri-Temporal	Manual	N	Ecol (No Field Obs)	Ecosystem Function	Productivity/Cycling
26	Lau et al	[100]	2008	Australia	Bauxite	Aerial Hyper	Aerial_Hyperspec	Site Scale	Uni-Temporal	NA	Y	Ecol (Field Obs)	Physical Conditions	Water Chemo-Physical
27	Lévesque & Staenz	[82]	2008	Canada	Metalliferous	Aerial Hyper	Aerial_Hyperspec	Site Scale	Tri-Temporal	Unsupervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
28	Richter et al	[101]	2008	Canada	Metalliferous	Aerial Hyper	Aerial_Hyperspec	Site Scale	Uni-Temporal	Supervised	Y	Land Cover	Structural Diversity	Spatial Mosaic
29	Yang	[102]	2008	USA	Coal	EO Low	Landsat	Site Scale	Tri-Temporal	Supervised	Y	Land Cover	Structural Diversity	Spatial Mosaic
30	Lu et al	[103]	2009	China	Coal	EO Low	EO-1_Hyperion	Site Scale	Uni-Temporal	NA	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
31	Townsend et al	[79]	2009	USA	Coal	EO Low	Landsat	Regional	Decadal	Unsupervised	N	Land Cover	Structural Diversity	Spatial Mosaic

Table A2. Cont.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
32	Wei et al	[104]	2009	China	Coal	EO Low	Landsat	Site Scale	Decadal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
33	Sonwalkar et al	[105]	2010	USA	Metalliferous	EO Low	MODIS	Site Scale	Multi-Temporal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
34	Spyropoulos et al	[106]	2010	Greece	Metalliferous	EO Low	Landsat	Site Scale	Tri-Temporal	Supervised	N	DSS	NA	NA
35	Demirel et al	[67]	2011	Turkey	Coal	EO High	IKONOS_&_Quickbird	Site Scale	Bi-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
36	Demirel et al	[68]	2011	Turkey	Coal	EO High	IKONOS_&_Quickbird	Site Scale	Bi-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
37	Erener	[59]	2011	Turkey	Coal	EO Low	Landsat	Regional	Tri-Temporal	Manual	N	Ecol (No Field Obs)	Ecosystem Function	Productivity/Cycling
38	Procházka et al	[107]	2011	Czech Republic	Coal	EO Low	Landsat	Site Scale	Uni-Temporal	Unsupervised	Y	Ecol (Field Obs)	External Exchanges	Landscape Flows
39	Sun et al	[108]	2011	China	Coal	Field Hyper	Field_Hyperspec	Block Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Species Composition	Desirable Plants
40	Bao et al	[69]	2012	China	Coal	EO High	Quickbird	Site Scale	Uni-Temporal	Manual	N	Ecol (No Field Obs)	Species Composition	Desirable Plants
41	Bodlak et al	[28]	2012	Czech Republic	Coal	EO Low	Landsat	Site Scale	Bi-Temporal	Manual	Y	Ecol (Field Obs)	External Exchanges	Landscape Flows
42	Brom et al	[66]	2012	Czech Republic	Coal	EO Low	Landsat	Site Scale	Decadal	Manual	N	Ecol (No Field Obs)	External Exchanges	Landscape Flows
43	Sen et al	[32]	2012	USA	Coal	EO Low	Landsat	Regional	Decadal	Supervised	N	Ecol (No Field Obs)	Ecosystem Function	Productivity/Cycling
44	Fletcher & Erskine	[74]	2013	Australia	Coal	Drone	Drone	Block Scale	Uni-Temporal	Manual	N	Ecol (No Field Obs)	Structural Diversity	All vegetation strata
45	Lemke et al	[60]	2013	USA	Coal	EO Low	Landsat	Regional	Decadal	Manual	Y	Ecol (Field Obs)	Absence of Threats	Invasive Species
46	Oparin et al	[62]	2013	Russia	Coal	EO Low	Landsat	Site Scale	Bi-Temporal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
47	Petropoulos et al	[56]	2013	Greece	Quarry	EO Low	Landsat	Regional	Tri-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic

Table A2. Cont.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
48	Raval et al	[70]	2013	Australia	Coal	EO High	WorldView	Site Scale	Uni-Temporal	Manual	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic
49	Antwi et al	[109]	2014	Germany	Coal	EO Low	Landsat	Regional	Decadal	Supervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
50	Bao et al	[31]	2014	Australia	Metalliferous	EO Med	SPOT	Site Scale	Uni-Temporal	GEOBIA	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
51	Bao et al	[44]	2014	Australia	Metalliferous	EO Med	SPOT	Site Scale	Multi-Temporal	Manual	N	Ecol (No Field Obs)	Ecosystem Function	Productivity/Cycling
52	Maxwell et al	[23]	2014	USA	Coal	Aerial LiDAR	Aerial_LiDAR	Site Scale	Uni-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
53	Maxwell et al	[110]	2014	USA	Coal	Aerial Optical	Aerial_Optical	Site Scale	Uni-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
54	Wang et al	[64]	2014	China	Coal	EO Low	Landsat	Regional	Decadal	GEOBIA	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
55	Zhang et al	[111]	2014	Canada	Oil Sands	EO Med	SPOT	Site Scale	Multi-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
56	Badreldin & Sanchez-Azofeifa	[112]	2015	Canada	Coal	Terrest LiDAR	Terrest LiDAR	Site Scale	Decadal	Manual	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
57	Li et al	[113]	2015	USA	Coal	EO Low	Landsat	Regional	Decadal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
58	Li et al	[114]	2015	USA	Coal	EO Low	Landsat	Regional	Decadal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
59	Maxwell & Warner	[72]	2015	USA	Coal	Aerial Optical	Aerial_Optical	Regional	Uni-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
60	Maxwell et al	[73]	2015	USA	Coal	EO Med	RapidEye	Site Scale	Uni-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
61	Szostak et al	[83]	2015	Poland	Sulfur	EO Low	Landsat	Site Scale	Bi-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
62	Tong et al	[115]	2015	China	Phosphate	Drone	Drone	Site Scale	Uni-Temporal	GEOBIA	N	Land Cover	Structural Diversity	Spatial Mosaic
63	Bao et al	[116]	2016	China	Coal	EO High	WorldView	Site Scale	Uni-Temporal	GEOBIA	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic

Table A2. Cont.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
64	Götze et al	[117]	2016	Czech Republic	Coal	Aerial Hyper	Aerial_Hyperspec	Site Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Physical Conditions	Substrate Chemical
65	Karan et al	[118]	2016	India	Coal	EO Low	Landsat	Site Scale	Bi-Temporal	Supervised	Y	Land Cover	Structural Diversity	Spatial Mosaic
66	Lechner, Kassulke & Unger	[87]	2016	Australia	Coal	Aerial Optical	Aerial_Optical	Regional	Uni-Temporal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
67	Liu	[119]	2016	China	Coal	EO Low	Landsat	Site Scale	Decadal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
68	Chen et al	[43]	2017	China	Coal	EO Low	MODIS	Regional	Multi-Temporal	Manual	Y	Ecol (Field Obs)	External Exchanges	Landscape Flows
69	Esposito	[120]	2017	Italy	Quarry	Drone	Drone	Block Scale	Bi-Temporal	NA	N	Land Cover	Structural Diversity	Spatial Mosaic
70	LeClerc & Wiersma	[81]	2017	Canada	Metalliferous	EO Low	Landsat	Regional	Decadal	Supervised	Y	Ecol (Field Obs)	External Exchanges	Habitat links
71	Macfarlane et al	[121]	2017	Australia	Bauxite	EO Low	Landsat	Regional	Decadal	Manual	Y	Theoretical	Structural Diversity	Spatial Mosaic
72	McKenna et al	[30]	2017	Australia	Coal	Drone	Drone	Block Scale	Bi-Temporal	Supervised	N	Ecol (No Field Obs)	External Exchanges	Landscape Flows
73	Oliphant et al	[61]	2017	USA	Coal	EO Low	Landsat	Site Scale	Multi-Temporal	Supervised	Y	Ecol (Field Obs)	Absence of Threats	Invasive Species
74	Padmanaban et al	[42]	2017	Germany	Coal	EO Low	Landsat	Site Scale	Multi-Temporal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
75	Yang et al	[71]	2017	China	Coal	EO High	GeoEye-1	Site Scale	Uni-Temporal	Manual	Y	Ecol (Field Obs)	Ecosystem Function	Habitat & Interactions
76	Zenkov et al	[57]	2017	Bulgaria	Coal	EO Low	Landsat	Site Scale	Decadal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
77	Bujalsky et al	[122]	2018	Czech Republic	Coal	Aerial Hyper	Aerial_Hyperspec	Site Scale	Uni-Temporal	Manual	N	Ecol (No Field Obs)	External Exchanges	Landscape Flows
78	Chasmer et al	[123]	2018	Canada	Oil Sands	EO Med	SPOT	Site Scale	Multi-Temporal	Manual	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
79	Chen et al	[19]	2018	NA	NA	NA	NA	NA	NA	NA	NA	Review	NA	NA

Table A2. Cont.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
80	Correa et al	[124]	2018	Brazil	Metalliferous	EO Low	MODIS	Site Scale	Multi-Temporal	NA	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
81	Gastauer et al	[125]	2018	NA	NA	NA	NA	NA	NA	NA	NA	Review	NA	NA
82	McKenna et al	[29]	2018	Australia	Coal	EO High	WorldView	Block Scale	Tri-Temporal	Supervised	Y	Ecol (Field Obs)	Ecosystem Function	Resilience/recruitment
83	Whiteside & Bartolo	[75]	2018	Australia	Uranium	Drone	Drone	Block Scale	Tri-Temporal	GEOBIA	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic
84	Yang et al	[126]	2018	USA	Coal	EO Low	Landsat	Regional	Decadal	Manual	N	Ecol (No Field Obs)	Ecosystem Function	Habitat & Interactions
85	Yang et al	[65]	2018	Australia	Coal	EO Low	Landsat	Regional	Decadal	Spectral Time-Series	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
86	Zenkov et al	[127]	2018	Russia	Iron Ore	EO Low	Landsat	Site Scale	Bi-Temporal	Manual	N	Land Cover	Structural Diversity	Spatial Mosaic
87	Bao et al	[24]	2019	China	Coal	SAR	SAR	Block Scale	Uni-Temporal	Manual	Y	Ecol (Field Obs)	Ecosystem Function	Productivity/Cycling
88	Buters et al	[20]	2019	NA	NA	NA	NA	NA	NA	NA	NA	Review	NA	NA
89	Dlamini et al	[58]	2019	South Africa	Mineral Sand	EO Low	Landsat	Site Scale	Decadal	Spectral Time-Series	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic
90	Erskine et al	[89]	2019	Australia	Uranium	EO Low	Landsat	Site Scale	Decadal	NA	Y	Ecol (Field Obs)	External Exchanges	Landscape Flows
91	Isokangas et al	[76]	2019	Finland	Metalliferous	Drone	Drone	Block Scale	Uni-Temporal	Manual	Y	Ecol (Field Obs)	Absence of Threats	Contamination
92	Johansen, Erskine & McCabe	[77]	2019	Australia	Coal	Drone	Drone	Block Scale	Tri-Temporal	GEOBIA	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
93	Kun	[128]	2019	Turkey	Coal	Drone	Drone	Block Scale	Uni-Temporal	Manual	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
94	Lechner et al	[49]	2019	PNG_&_Laos	Metalliferous	EO Low	Landsat	Regional	Decadal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
95	Moudry et al	[25]	2019	Czech Republic	Coal	Drone	Drone	Block Scale	Uni-Temporal	Manual	Y	Ecol (Field Obs)	Structural Diversity	All vegetation strata

Table A2. Cont.

No.	Author	Ref	Year	Country	Commodity Summary	Sensor Summary	Craft Primary	Spatial Extent	Temporal Scale	Classification Type	Field Obs	Study Type 1	Study Type 2 (Attributes)	Study Type 2 (Sub-Attributes)
96	Padro et al	[85]	2019	Spain	Quarry	Drone	Drone	Block Scale	Uni-Temporal	Supervised	Y	Ecol (Field Obs)	Structural Diversity	Spatial Mosaic
97	Vasuki et al	[129]	2019	Australia	Bauxite	EO Low	Landsat	Regional	Decadal	Supervised	N	Land Cover	Structural Diversity	Spatial Mosaic
98	Xu et al	[130]	2019	China	Coal	EO Med	SPOT	Regional	Tri-Temporal	Supervised	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic
99	Zhang et al	[86]	2019	China	Coal	EO Low	Landsat	Site Scale	Decadal	Supervised	N	Ecol (No Field Obs)	Structural Diversity	Spatial Mosaic

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